IN THE CLAIMS

1. (currently amended) A system for automatically decomposing an image sequence, comprising a computer-readable storage medium storing a program that when executed ~~using a computer to perform~~ performs the following process actions:

providing an image sequence of at least one image frame of a scene;

providing only a preferred number of classes of objects to be identified within the image sequence;

automatically decomposing the image sequence into the preferred number of classes of objects in near real-time, using probabilistic inference and learning to compute a single set of model parameters comprising the mean visual appearance and variance of each class in the image sequence.

2. (original) The system of Claim 1 wherein providing the preferred number of objects comprises specifying the preferred number of classes of objects via a user interface.

3. (original) The system of Claim 1 wherein decomposing the image sequence into the preferred number of objects comprises automatically learning a 2-dimensional model of each object class.

4. (original) The system of Claim 3 wherein the model employs a latent image and a translation variable in learning each object class.

5. (original) The system of Claim 1 wherein automatically decomposing the image sequence into the preferred number of object classes comprises performing an inferential probabilistic analysis of each image frame for

identifying the preferred number of object class appearances within the image sequence.

6. (original) The system of Claim 5 wherein performing an inferential probabilistic analysis of each image frame comprises performing a variational generalized expectation-maximization analysis of each image frame of the image sequence, wherein the expectation-maximization analysis employs a Viterbi algorithm in a process of filling in values of hidden variables in a model describing the object class.

7. (original) The system of Claim 6 wherein the model describing the object class employs a latent image and a translation variable in filling in said hidden variables.

8. (original) The system of Claim 6 wherein an expectation step of the generalized expectation-maximization analysis maximizes a lower bound on a log-likelihood of an image frame by inferring variational approximations of variational parameters.

9. (original) The system of Claim 8 wherein a maximization step of the generalized expectation-maximization analysis automatically adjusts object model parameters in order to maximize the lower bound on the log-likelihood of the image frame.

10. (original) The system of Claim 9 wherein the expectation step and the maximization step are performed once for each image in said image sequence.

11. (original) The system of Claim 8 wherein automatic computation of the expectation step is accelerated by using an FFT-based inference analysis.

12. (original) The system of Claim 11 wherein the FFT-based inference analysis is performed on variables that are converted into a coordinate system wherein transforms applied to those variables are represented by shift operations.

13. (original) The system of Claim 8 wherein automatic computation of the expectation step is accelerated by using a Viterbi analysis.

14. (original) The system of Claim 1 wherein automatically decomposing the image sequence into the preferred number of object classes comprises performing a probabilistic variational expectation-maximization analysis.

15. (original) The system of Claim 14 wherein the variational expectation maximization analysis comprises:

forming a probabilistic model having variational parameters representing posterior distributions;

initializing said probabilistic model;

inputting an image frame from the image sequence;

computing a posterior given observed data in said image sequence; and

using the posterior of the observed data to update the probabilistic model parameters.

16. (original) The system of Claim 15 wherein the variational expectation-maximization analysis further comprises:

outputting the model parameters.

17. (original) The system of Claim 15 further comprising incrementing to the next image frame in said image sequence and repeating the actions after initializing the probability model until the end of the image sequence has been reached.

18. (original) The system of Claim 1 further comprising a generative model which includes a set of model parameters that represent the entire image sequence.

19. (original) The system of Claim 1 further comprising a generative model which includes a set of model parameters that represent the images of the image sequence processed to that point.

20. (original) The system of Claim 19 wherein the model parameters include:

a prior probability of at least one object class; and

means and variances of object appearance maps.

21. (original) The system of Claim 20 wherein the model further comprises observation noise variances.

22. (original) The system of Claim 19 further comprising automatically reconstructing a representation of the image sequence from the generative model, wherein the representation comprises the preferred number of object classes.

23. (currently amended) A computer-implemented process for automatically generating a representation of an object in at least one image sequence, comprising a computer-readable storage medium storing a program that when executed is used to~~using a computer to~~:

acquire at least one image sequence, each image sequence having at least one image frame;

in near real-time automatically decompose each image sequence into a generative model with each generative model ~~including~~ comprising a set of model parameters comprising the mean visual appearance and variance of each class in the image sequence being decomposed, ~~that represent at least one object class for each image sequence~~ using an expectation-maximization analysis that employs a Viterbi analysis.

24. (original) The computer-implemented process of Claim 23 wherein the number of object classes learned for each image sequence is input via a user interface.

25. (original) The computer-implemented process of Claim 23 wherein the model parameters of each generative model include an object class appearance map, and a prior probability of at least one object class.

26. (original) The computer-implemented process of Claim 25 wherein the object class appearance map for each generative model includes means and variances of that object class appearance map.

27. (original) The computer-implemented process of Claim 23 wherein a latent image and a translation variable are employed in determining said generative model.

28. (original) The computer-implemented process of Claim 23 wherein an expectation step of the generalized expectation-maximization analysis maximizes a lower bound on a log-likelihood of each image frame by inferring approximations of variational parameters.

29. (original) The computer-implemented process of Claim 23 wherein the maximization step of the generalized expectation-maximization analysis

automatically adjusts model parameters in order to maximize a lower bound on a log-likelihood of each image frame.

30. (original) The computer-implemented process of Claim 23 wherein the expectation-maximization analysis comprises:

forming a probabilistic model having variational parameters representing posterior distributions;

initializing said probabilistic model;

inputting an image frame from the image sequence;

computing a posterior given observed data in said image sequence; and

using the posterior of the observed data to update the probabilistic model parameters.

31. (original) The computer-implemented process of Claim 30 wherein the expectation-maximization analysis further comprises:

outputting the model parameters.

32. (original) The computer-implemented process of Claim 23 wherein computation of the expectation step is accelerated using an FFT-based inference analysis.

Claims 33-38 (cancelled).